NBA(National Basketball Association)

Understanding Data

Position Of Player

PG-- *Point guard* **SF**-- *Small forward* **SG**-- *Shooting guard* **PF**-- *Power forward* **C**-- *Center*

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [3]:
```
#Reading the CSV files
df=pd.read_csv("nba.csv",encoding='unicode_escape')
```

In [10]:
```
df.shape
```

Out[10]:
```
(457, 8)
```

In [11]:
```
df.head()
```

Out[11]:

	Name	Team	Number	Position	Age	Weight	College	Salary
0	Avery Bradley	Boston Celtics	0	PG	25	180	Texas	7730337.0
1	Jae Crowder	Boston Celtics	99	SF	25	235	Marquette	6796117.0
2	John Holland	Boston Celtics	30	SG	27	205	Boston University	NaN
3	R.J. Hunter	Boston Celtics	28	SG	22	185	Georgia State	1148640.0
4	Jonas Jerebko	Boston Celtics	8	PF	29	231	NaN	5000000.0

In [12]:
```
df.tail()
```

Out[12]:

	Name	Team	Number	Position	Age	Weight	College	Salary
452	Trey Lyles	Utah Jazz	41	PF	20	234	Kentucky	2239800.0
453	Shelvin Mack	Utah Jazz	8	PG	26	203	Butler	2433333.0
454	Raul Neto	Utah Jazz	25	PG	24	179	NaN	900000.0
455	Tibor Pleiss	Utah Jazz	21	C	26	256	NaN	2900000.0
456	Jeff Withey	Utah Jazz	24	C	26	231	Kansas	947276.0

In [14]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 457 entries, 0 to 456
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Name      457 non-null    object 
 1   Team      457 non-null    object 
 2   Number    457 non-null    int64  
 3   Position  457 non-null    object 
 4   Age       457 non-null    int64  
 5   Weight    457 non-null    int64  
 6   College   373 non-null    object 
 7   Salary    446 non-null    float64
dtypes: float64(1), int64(3), object(4)
memory usage: 28.7+ KB
```

Data Cleaning

In [16]:
```
pd.isnull(df).sum()
```

Out[16]:
```
Name         0
Team         0
Number       0
Position     0
Age          0
Weight       0
College     84
Salary      11
dtype: int64
```

In [17]:
```
df.dropna(inplace=True)
```

In [18]:
```
df.drop_duplicates(inplace=True)
```

In [19]:
```
pd.isnull(df).sum()
```

Out[19]:
```
Name        0
Team        0
Number      0
Position    0
Age         0
Weight      0
College     0
Salary      0
dtype: int64
```

Data Transformation

Creating a new column (BMI) using a fixed Height Value

In [21]:
```
fix_height= 75
```

In [22]:
```
df.columns
```

Out[22]:
```
Index(['Name', 'Team', 'Number', 'Position', 'Age', 'Weight', 'College',
       'Salary'],
      dtype='object')
```

In [24]:
```
df['BMI']=(df['Weight']/(fix_height**2))*703
```

In [25]:
```
df.columns
```

Out[25]:
```
Index(['Name', 'Team', 'Number', 'Position', 'Age', 'Weight', 'College',
       'Salary', 'BMI'],
      dtype='object')
```

In [26]:
```
df.head()
```

Out[26]:

	Name	Team	Number	Position	Age	Weight	College	Salary	BMI
0	Avery Bradley	Boston Celtics	0	PG	25	180	Texas	7730337.0	22.496000
1	Jae Crowder	Boston Celtics	99	SF	25	235	Marquette	6796117.0	29.369778
2	John Holland	Boston Celtics	30	SG	27	205	Boston University	NaN	25.620444
3	R.J. Hunter	Boston Celtics	28	SG	22	185	Georgia State	1148640.0	23.120889
4	Jonas Jerebko	Boston Celtics	8	PF	29	231	NaN	5000000.0	28.869867

EXPLORATORY DATA ANALYSIS

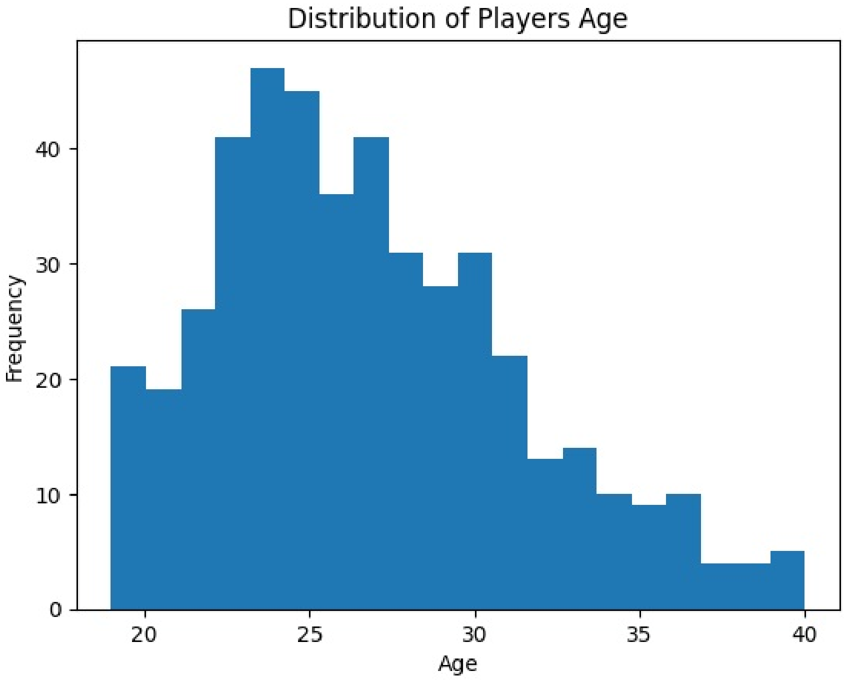
In [29]:
```
df[['Age','Weight','BMI']].describe()
```

Out[29]:

	Age	Weight	BMI
count	457.000000	457.000000	457.000000
mean	26.938731	221.522976	27.685449
std	4.404016	26.368343	3.295457
min	19.000000	161.000000	20.121422
25%	24.000000	200.000000	24.995556
50%	26.000000	220.000000	27.495111
75%	30.000000	240.000000	29.994667
max	40.000000	307.000000	38.368178

From above chart we can get information the Mean of Age and BMI is 27 and 28 approx respectively

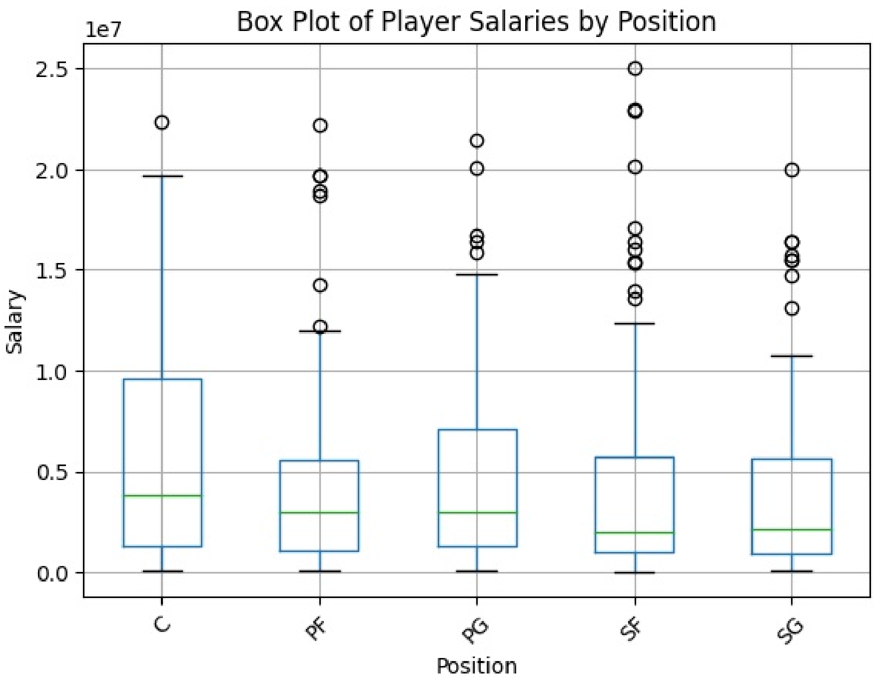
In [34]:
```
plt.hist(df['Age'],bins=20)
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.title('Distribution of Players Age')
plt.show()
```



From the above histogram it shows distributions of Players age with intervals(20)

In [35]:
```
plt.figure(figsize=(10, 6))
df.boxplot(column='Salary', by='Position')
plt.ylabel('Salary')
plt.title('Box Plot of Player Salaries by Position')
plt.suptitle('')
plt.xticks(rotation=45)
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```



In [36]:

```
# Scatter plot of 'age' vs. 'salary' by position
plt.figure(figsize=(10, 6))
colors = {'PG': 'red', 'SG': 'blue', 'SF': 'green', 'PF': 'purple', 'C': 'orange'}
plt.scatter(df['Age'], df['Salary'], c=df['Position'].map(colors), alpha=0.5)
plt.xlabel('Age')
plt.ylabel('Salary')
plt.title('Age vs. Salary by Position')
plt.legend(colors)
plt.show()
```

In [5]:
```
#Top Players in terms of salary
top_players=df.nlargest(10,'Salary')
print(top_players)
```

```
              Name                   Team  Number Position  Age  Weight  \
109    Kobe Bryant     Los Angeles Lakers      24       SF   37     212
169   LeBron James    Cleveland Cavaliers      23       SF   31     250
33   Carmelo Anthony        New York Knicks       7       SF   32     240
251   Dwight Howard        Houston Rockets      12        C   30     265
339      Chris Bosh             Miami Heat       1       PF   32     235
100      Chris Paul   Los Angeles Clippers       3       PG   31     175
414    Kevin Durant  Oklahoma City Thunder      35       SF   27     240
164    Derrick Rose          Chicago Bulls       1       PG   27     190
349     Dwyane Wade             Miami Heat       3       SG   34     220
23       Brook Lopez          Brooklyn Nets      11        C   28     275

          College      Salary
109           NaN  25000000.0
169           NaN  22970500.0
33       Syracuse  22875000.0
251           NaN  22359364.0
339  Georgia Tech  22192730.0
100   Wake Forest  21468695.0
414         Texas  20158622.0
164       Memphis  20093064.0
349     Marquette  20000000.0
23       Stanford  19689000.0
```

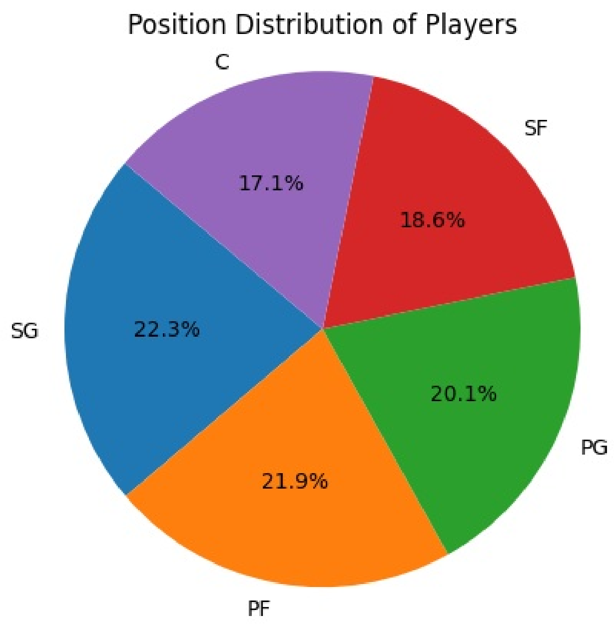
The above data shows the top-10 players having highest salary

In [8]:
```
#Top colleges showing participation strength
top_college=df['College'].value_counts().nlargest(5)
print(top_college)
```

```
College
Kentucky          22
Duke              20
Kansas            18
North Carolina    16
UCLA              15
Name: count, dtype: int64
```

From above analysis we can view the Top college in participation is Kentucky

In [15]:
```
#Position Distribution using charts
position_counts = df['Position'].value_counts()
plt.pie(position_counts, labels=position_counts.index, autopct='%1.1f%%', startangle=140)
plt.title('Position Distribution of Players')
plt.axis('equal')
plt.show()
```

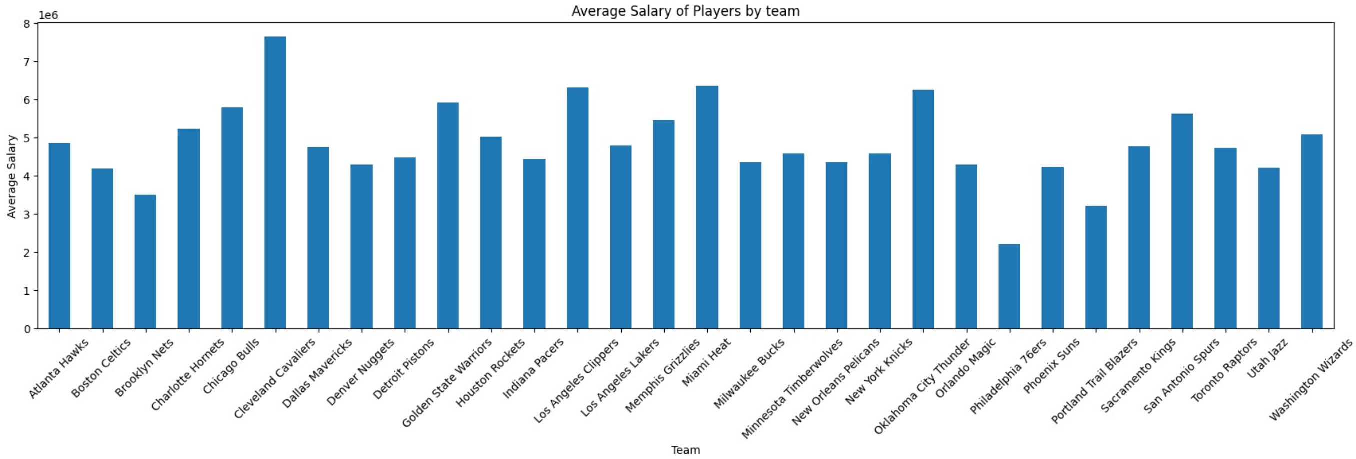


Above Pie charts gives the visuals that the top position distribution of players goes to SG followed by PF,PG,SF,C

In [16]:
```
#Team Analysis:
avg_salary_by_team=df.groupby('Team')['Salary'].mean()
print(avg_salary_by_team)
```

```
Team
Atlanta Hawks             4.860197e+06
Boston Celtics            4.181505e+06
Brooklyn Nets             3.501898e+06
Charlotte Hornets         5.222728e+06
Chicago Bulls             5.785559e+06
Cleveland Cavaliers       7.642049e+06
Dallas Mavericks          4.746582e+06
Denver Nuggets            4.294424e+06
Detroit Pistons           4.477884e+06
Golden State Warriors     5.924600e+06
Houston Rockets           5.018868e+06
Indiana Pacers            4.450122e+06
Los Angeles Clippers      6.323643e+06
Los Angeles Lakers        4.784695e+06
Memphis Grizzlies         5.467920e+06
Miami Heat                6.347359e+06
Milwaukee Bucks           4.350220e+06
Minnesota Timberwolves    4.593054e+06
New Orleans Pelicans      4.355304e+06
New York Knicks           4.581494e+06
Oklahoma City Thunder     6.251020e+06
Orlando Magic             4.297248e+06
Philadelphia 76ers        2.213778e+06
Phoenix Suns              4.229676e+06
Portland Trail Blazers    3.220121e+06
Sacramento Kings          4.778911e+06
San Antonio Spurs         5.629516e+06
Toronto Raptors           4.741174e+06
Utah Jazz                 4.204006e+06
Washington Wizards        5.088576e+06
Name: Salary, dtype: float64
```

In [25]:
```
plt.figure(figsize=(21,5))
avg_salary_by_team.plot(kind='bar')
plt.xlabel('Team')
plt.ylabel('Average Salary')
plt.title('Average Salary of Players by team')
plt.xticks(rotation=45)
plt.show()
```



Above chart shows visuals of Team(Cleveland Cavaliers) has highest salary among all teams

Conclusion

- From above data analysis we can conclude some interesting factors like Highest salary(Cleveland Cavaliers),most persons having position in SG
- Top player having highest salary is Kobe Bryant*

In [ ]:

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